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Determining socially optimal rates of nitrogen fertilizer application

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A B S T R A C T

Effective management of nitrogen (N) fertilizer is central to enhancing agricultural productivity, while improving water and air quality and mitigating climate change. Quantifying "socially optimal" rates of N fertilizer (i.e. maximizing net benefits to society while minimizing social costs) is a key component of any regulatory or incentive program designed to better manage N application. Here, we estimate spatially-explicit socially optimal N fertilizer application rates for corn in Minnesota that account for uncertainty, both in valuation techniques and model parameters. We find that socially optimal rates of N fertilizer application are between 0 and 161 kg ha^{-1}, whereas the private optimum is 165 kg ha^{-1}. Choice of valuation methods shifts the spatial configuration and magnitude of the socially optimal N application rates illustrating the importance of valuation method and assumptions. Even after accounting for uncertainty in valuation methods, we find reducing rates of N fertilizer application offers significant opportunities to improve social welfare. By internalizing the social costs of nitrogen, net social benefits of N could increase by over $1100 ha^{-1}, even while accounting for declines in agricultural yields.

1. Introduction

Modern agricultural practices have dramatically increased crop production, but have also caused widespread environmental degradation (Matson et al., 1997; Foley et al., 2005). Since 1970, reactive nitrogen (N) creation has increased by over 120% (Galloway et al., 2008), largely driven by increased inorganic N fertilizer application to meet growing global demand for agricultural commodities (Vitousek et al., 1997). However, excess levels of N in the environment have resulted in the degradation of air and water quality, exacerbation of climate change, and damages to human health (Erisman et al., 2013). These costs have historically been ignored or underestimated, particularly relative to the benefits of increased crop yields (Compton et al., 2011). Accounting for these costs in policies, payment schemes, or programs designed to influence land management offers the potential to mitigate these tradeoffs and substantially improve environmental and social outcomes, especially in agriculturally dominated landscapes (Polasky et al., 2011; Pennington et al., 2017).

Effectively managing the tradeoffs inherent in N use requires information on the true marginal benefits and costs of N to both private landowners and society. The benefits of N fertilizer application, measured in terms of improved crop yields, are easily quantified based on the market value of crop production. Regardless of how corn is used, its value is reflected by its market prices. We define the privately optimal rate of N fertilizer application as the rate that maximizes yield benefits for private producers, accounting for the market price of N fertilizer (i.e. the agronomic optimum). In contrast, the social costs of N (SCN) are not captured in market prices for fertilizer or agricultural commodities and are incurred primarily by the public downwind or downstream of agricultural N application. In part due to these differences, the value of the SCN are less well understood and more uncertain relative to the value of corn production (Compton et al., 2011). We define the socially optimal rate of N fertilizer application as the rate that maximizes net benefits of N to society by accounting for the private benefits and costs of N.

Quantifying the externalized SCN is challenging because N is lost to aquatic, regional atmospheric, and global atmospheric pools in a variety of forms. These loss pathways are associated with damages to water quality, air quality, and climate change, respectively, that occur over heterogeneous spatial and temporal scales (Erisman et al., 2013). Valuing these damages requires tracking several forms of N across space to endpoints where people are impacted. Multiple groups of people suffer from N-related damages and often respond differently to these impacts depending on their preferences and social vulnerability (Lewandowski et al., 2008).

Monetary valuation and cost-benefit analysis are widely used

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decision-support tools for comparing and aggregating the costs and benefits of N. Several recent studies have shown that the SCN are potentially large (e.g. Keeler et al., 2016), possibly exceeding \$440 billion yr^{-1} in the United States (Sobota et al., 2015) and €320 billion yr^{-1} in Europe (Sutton et al., 2011). These published estimates of the SCN range by several orders of magnitude, highlighting considerable uncertainty in the true value of N-related impacts. Improving understanding of the sources of uncertainty in the SCN will enhance the credibility of this information in decision-making processes and increase the likelihood of its uptake in regulatory or policy tools. We address this need through a rigorous consideration of uncertainty in model estimates, including assessing the sensitivity of SCN to the choice of valuation approach and uncertainty in parameter estimates.

The diversity of N loss pathways and endpoints at which damages occur makes it challenging to integrate the multiple SCN into a single cost metric. Non-market valuation techniques allow for estimation of the multiple SCN in monetary terms, however these methods vary widely in their assumptions and model structure (Wegner and Pascual, 2011). For example, Keeler et al. (2016) valued the costs of atmospheric forms of N (i.e. NO_x and NH_3) using methods based on stated preferences for avoiding health impacts from reduced air quality, whereas costs associated with aquatic forms of N (i.e. NO_3^-) were valued using replacement costs for contaminated drinking water. These two sets of models are based on fundamentally different assumptions about human behaviors and preferences. Aggregating the results from these distinct methods into a single metric makes it difficult to interpret the SCN and understand the distributional impacts of different N-related costs on different groups.

Another key source of uncertainty in the SCN arises from the parametric relationships that drive the model (Refsgaard et al., 2007). We represent model parameters with probability distributions in order to provide a more complete understanding of the range, likelihood, and magnitude of the SCN. We demonstrate the value of this information by showing how parametric uncertainty may alter effective N management strategies under various levels of risk tolerance. For example, the epidemiological research linking the relative risk of nitrate exposure in drinking water and various forms of cancer has found both positive, negative, and neutral effects (Ward et al., 2010). As such, the SCN will vary depending on risk tolerance and how these findings are interpreted. The SCN will be higher when N is assumed to increase cancer risks; inversely, the SCN will be lower when N is assumed to have neutral or positive impacts on health.

The overall aim of this study is to improve N management strategies that balance tradeoffs among crop production, the protection of water and air quality, and climate change mitigation. To achieve this goal, we ask two sets of questions:

1) What are the marginal social costs and benefits of N? How uncertain are these estimates and what are the primary sources of uncertainty underlying the valuation of these costs and benefits?
2) What are the privately and socially optimal rates of N fertilizer application? How do these vary spatially and by valuation approach, and what is their impact on society?

We answer these questions using a spatially explicit modeling framework that integrates biogeochemical and economic processes and accounts for variation in non-market valuation techniques and parametric uncertainty.

2. Methods

2.1. Overview

We determined socially optimal rates of N fertilizer application by evaluating the private and social costs and benefits of N and identifying the rate at which net benefits of N to society are maximized. We conducted this analysis in the state of Minnesota (MN), which produces over 10% of corn grown in the United States (U.S.) (U.S. Department of Agriculture – National Agricultural Statistics Service, 2013). While crop yields in MN are N-limited and substantially increase with nitrogen fertilization, groundwater aquifers in several regions of the state are highly vulnerable to nitrate contamination (Porcher, 1989; Keeler and Polasky, 2014). Therefore, N loss from fertilizer application creates tradeoffs between benefits to agricultural production and costs in terms of clean air and water and climate change mitigation. Private benefits of N were calculated based on the market value of increases in corn yields minus the cost of fertilizer to farmers. We focused on the SCN caused by groundwater nitrate (NO_3^-) contamination, air pollution by small particulate matter ($PM_{2.5}$) formed from ammonia (NH_3) and N oxides (NO_x), and global climate change from nitrous oxide (N_2O) emissions. Benefits and costs were both calculated at the county-level to account for the spatial heterogeneity in the SCN and to match the resolution of publically available datasets. We then assessed how variation in the assumptions underlying the non-market valuation functions used to value these costs and benefits on management decisions. We also computed the probability distribution of model outputs and parameters' contribution to variance with a Monte Carlo simulation. Using a cost-benefit analysis framework, we then estimated socially optimal rates of N fertilizer application and the associated impacts of internalizing the SCN on private and social returns to N.

2.2. Conceptual framework for estimating the SCN

We adopted the conceptual framework proposed by Keeler et al. (2016) for estimating the SCN. The framework explicitly accounts for the costs (C) of exposure to elevated concentrations of N for differentiated forms of N (j) applied at specific locations (i). This framework accounts for the complex biogeochemistry of the N cycle, where a single unit of reactive N is transported, transformed, and accrues damages over time and space. We made several simplifying assumptions regarding the transportation and transformation of N over time to make this framework empirically tractable. Limited by data availability and current understanding of the N cycle, we only estimated costs associated with the first transformation of the N cascade (see Galloway et al., 2003) from fertilizer to atmospheric or aquatic pools (Eq. (1)), and ignore any subsequent transformations of N.

$$SCN_i = \sum_{j=1}^{J} \sum_{i=1}^{I} N_{ij} C_{ij} \tag{1}$$

N_{ij} and C_{ij} both depend on where N is applied (i = 1), the location of the endpoints (i = 1, 2, …, n), and its form at those endpoints (j = N_2O, NO_x, NH_3, or NO_3^-). N_{ij} is a function of the allocation of N loss into the appropriate concentration (i.e. ppm, $\mu g\, m^{-3}$) and form, transport of N across the landscape to endpoints of residence, and transformation and attenuation of N between the source location and the endpoints. C_{ij} is a function of human populations' exposure to N at the endpoints, the social vulnerability and preferences for various alternatives of the exposed populations, and the marginal damages incurred by the populations' exposure to N in form j.

Using this framework, we estimated the marginal SCN applied as fertilizer in each county in MN as a function of damages to water and air quality and climate change. Water quality damages reflect costs incurred to drinking water consumers who rely on groundwater in MN, air quality damages are assessed regionally based on health impacts incurred in MN and downwind in adjacent states, and climate change damages reflect global costs. Most of the drinking water in this region is from groundwater sources, and therefore, most of the exposure and associated health impacts are linked to N in groundwater rather than surface water. Air pollution and greenhouse gas emissions from fertilizer application also represent significant damages and have well-established approaches for evaluating costs. In addition to these damages,

Table 1
Valuation methodologies used to evaluate the costs and benefits of N fertilizer application.

Benefit/Cost	Model code	Measured Value	References
Increased crop yields	Y1	Net private returns from increased crop yields	Iowa State University Agronomy Extension and Outreach (2017)
Households' exposure to NO_3^- leached to groundwater	W1	Willingness to pay for nitrate-free drinking water	Crutchfield et al. (1997)
	W2	Willingness to pay for nitrate-safe drinking water	Crutchfield et al. (1997)
	W3	Cost of least cost treatment option for contamination	Keeler and Polasky (2014)
	W4	Weighted-average cost of observed responses to contamination (assuming no health impacts)	Keeler and Polasky (2014)
	W5	Weighted-average cost of observed responses to contamination (assuming drinking water with elevated NO_3^- is associated with premature mortality)	This paper
	W6	Weighted-average cost of observed responses to contamination (assuming drinking water with elevated NO_3^- is associated with lost QALYs)	van Grinsven et al. (2010)
Populations' exposure to $PM_{2.5}$ formed from atmospheric NH_3 and NO_x emissions	A1	Cost of premature mortalities from exposure to elevated $PM_{2.5}$	Tessum et al. (2017)
	A2	Cost of lost QALYs from exposure to elevated $PM_{2.5}$	Sutton et al. (2011)
Damages via climate change from N_2O emissions	C1	Cost of avoided damages from reducing N_2O emissions	Marten and Newbold (2012); U.S. Interagency Working Group (2015)

a large proportion of N fertilizer is also lost to surface water and may have substantial impacts on aquatic ecosystems (Schlesinger, 2009). However, the economic damages of these impacts are largely unknown (Rabotyagov et al., 2014), thus precluding the estimation of these values in this study.

2.3. Estimating households' exposure to N loss

We estimated the exposure to elevated concentrations of nitrate (NO_3^-) in groundwater for MN households that rely on private drinking water wells. Using domestic well data from the County Well Index (CWI), a spatially explicit database of wells drilled since 1974 with known NO_3^- concentrations, we establish a baseline for nitrate groundwater contamination in MN. For wells with multiple NO_3^- concentrations recordings, we only used the maximum-recorded (as opposed to the average) concentration since the maximum contaminant level (MCL) set by the U.S. Environmental Protection Agency represents the highest allowable concentration allowed in drinking water. The CWI database contains 227,686 unique domestic wells with measured nitrate concentrations. However, there are a total of 512,721 households (assuming 2.2 individuals per household) in MN that rely on private wells for drinking water (Maupin et al., 2014). To estimate nitrate concentrations for the remaining privates well in MN with unknown nitrate concentrations, we imputed the missing data in the CWI database by randomly sampling with replacement at the county-level. This complete dataset of exposure to elevated concentrations of nitrate (NO_3^-) in groundwater implicitly accounts for differences in well depth and county-level spatial variation in soil and geological characteristics that affect the transport and attenuation of NO_3^- into groundwater. In order to account for households that rely on drinking water from public water suppliers, we combined this dataset with a dataset collected by Keeler et al. (2016) on NO_3^- concentrations in community and non-community public water supplies (see Keeler et al., 2016 for more details on this dataset).

We evaluated loss of N oxides (NO_x), ammonia (NH_3), and nitrous oxide (N_2O) from N fertilizer applied to farm fields using spatially homogeneous emissions factors. The emissions factors we used were drawn from national and global *meta*-analyses and were based on a weighted average of the proportions N fertilizer types applied by farmers in MN (Bierman et al., 2012). The emissions factors for NO_x, NH_3, and N_2O are 0.005 (Stehfest and Bouwman, 2006), 0.08 (Bouwman et al., 2006; Kusiima and Powers, 2010; U.S. Environmental Protection Agency, 2011), and 0.01(De Klein et al., 2006; Stehfest and Bouwman, 2006; Kusiima and Powers, 2010), respectively. Once N_2O is emitted to the atmosphere, we assumed there is no further attenuation along its flow path and that it mixes uniformly in the global atmospheric pool. As a result, damages from N_2O are independent of the spatial location of emissions. Using the Intervention Model for Air Pollution (InMAP), we estimated exposure to $PM_{2.5}$ formed from NO_x and NH_3 emissions. InMAP (available to download at http://spatialmodel.com/inmap) is an open-source spatially-explicit chemical transport model that simulates the annual-average transport, transformation, and removal of air emissions (Tessum et al., 2017). InMAP is more computationally efficient than other chemical transport models and only requires the input of the total annual emissions at a source location. The model treats the relationship between emissions and $PM_{2.5}$ deposition linearly, therefore we estimated the marginal damages of emissions by running InMAP using separate shapefiles of each county in MN with one unit of NH_3 and NO_x emissions. Each model run output a receptor matrix shapefile covering the entire U.S., where the size of the receptor cells varies depending on population density. Within each receptor, InMAP estimates elevated $PM_{2.5}$ concentrations and population density using U.S. Census data.

2.4. Estimating costs of elevated exposure to N

We estimated the costs of elevated exposure to N using several non-market valuation methodologies (Table 1). Each non-market valuation function converts exposure to an elevated form of N at an endpoint into costs using damage functions specific to the N form, damage, and exposed population. These valuation functions depend on a suite of parameters that we assembled from the literature (see Table S1) and assumptions regarding the preferences of and damages experienced by exposed populations. Models W5–W6 and A1–A2 explicitly account for increased risk of morbidity and mortality from elevated exposure to N (see Supplementary material for more detail). Except for model W5, all valuation models were adopted from past studies (Table 1). To our knowledge, this is the first study to evaluate health impacts from nitrate in terms of premature mortalities and to estimate the cost of these health impacts using the value of statistical life. We tested how different non-market valuation techniques affected the SCN by varying the modeling assumptions used to estimate the costs of exposure to NO_3^- leached to groundwater and exposure to $PM_{2.5}$ formed from atmospheric NH_3 and NO_x emissions. This is indicated in Table 1 by the model codes W1–W6 and A1–A2. The assumptions on which each valuation function relies are detailed in the Supplementary material. We then systematically test how estimates of the SCN are affected by the assumptions of the valuation functions and the uncertainty in the parameters.

2.5. Estimating parametric uncertainty and sensitivity

We constructed probability distributions of the valuation outputs using a Monte Carlo simulation. For each valuation function for each county in MN, we ran the Monte Carlo simulation over 1000 iterations, for a total of 874,000 unique outputs. After approximately 200 simulations, the standard deviation of the outputs plateaus (Fig. S2). For parameters with only one value estimate, we used that value as a constant across all iterations of the Monte Carlo simulation. For parameters with two value estimates, we fit a truncated normal distribution using the Scipy package version 0.17.0 in Python version 2.7. For parameters with more than two value estimates, we used the Fitter package version 1.0.4 in Python version 2.7 to fit 80 PDFs. We then selected the fitted PDF with least sum of squares error as the best-fit distribution. Under each simulation, parameters with two or more value estimates were randomly sampled from their best-fit PDFs. See SI Table 1 for a description of all parameters and their summary statistics and best-fit PDF.

We then conducted a sensitivity analysis to estimate the valuation functions' sensitivity to parametric uncertainty. We used the outputs of the Monte Carlo simulation to fit multivariate linear models relating the costs and benefits of N (Y) to the sampled parameters for each iteration of the Monte Carlo simulation (X_i) (Eq. (2)). We obtained the standardized regression coefficients β_i^2 by normalizing the slopes b_i (Eq. (3)) (Saltelli et al., 2005).

$$Y = \sum b_i X_i \tag{2}$$

$$\beta_i = b_i \frac{\sigma_{X_i}}{\sigma_Y} \tag{3}$$

The standardized regression coefficients β_i^2 indicate sensitivity by representing the first-order contribution to variance of the variable X_i to Y. This analysis was repeated for each valuation function, where a variable was only included in the linear model if it was an input to a particular valuation function.

2.6. Optimizing N fertilizer application rates

We optimized the rate of N fertilizer application to maximize private and social returns to N. The optimal rate of N fertilizer application to maximize private returns is where gross returns (the product of corn yields Y at application rate r and the price of corn P_c) minus private costs (the product of rate of application and the market price of N fertilizer) is maximized (Eq. (4)).

$$NR_p = \max(Y_r P_c - N_r P_N) \tag{4}$$

The optimal rate of N fertilizer application to maximize social returns is calculated similarly to the private optimum, except that the SCN for fertilizer applied at site i is subtracted. The SCN are specific to site i, but yields and the price on N remain spatially constant.

$$NR_{si} = \max(Y_r P_c - N_r P_N - N_r SCN_i) \tag{5}$$

Under the optimal rate of N fertilizer application to maximize social returns, we calculated loss to farmers based on decreased yields from reduced N fertilizer application.

3. Results

3.1. Variation in estimates of the SCN

The individual SCN vary widely due to parametric uncertainty, the spatial location of application, and the form of N loss (Fig. 1). Since the value estimates from the crop yield model (model Y1) and the climate change model (model C1) are spatially homogenous and rely on relatively fewer parametric relationships, their distributions are narrower. In comparison, estimates from the water and air quality models (models W1-W6 and A1-A2) exhibit wider distributions (Fig. 1). In general, the estimated costs of exposure to $PM_{2.5}$ are in general orders of magnitude greater than the costs of exposure to NO_3^- (Fig. 1). The median cost of exposure of NO_3^- is \$0.073 per kg N, while the median cost of exposure to $PM_{2.5}$ is \$0.54 per kg N. Exposure to NO_3^- can be avoided using replacement or remediation approaches, while exposure to $PM_{2.5}$ in the air is less easily avoided. In addition, the median value of benefits from crop yields exceed the median value for any of the social costs individually (Fig. 1).

Due to differing assumptions and model structures, the valuation outputs for the same category of damage costs vary by orders of magnitude. The median cost of damages from NO_3^- groundwater contamination ranges from \$0.005 to \$0.66 per kg N across models W1 to W6 and the median cost of damages from exposure to $PM_{2.5}$ ranges from \$0.28 to \$1.49 per kg N between models A1 and A2 (Fig. 1). The two WTP valuation models, models W1 and W2, represent the upper and lower bound costs of damages to groundwater quality, respectively, demonstrating the range in attitudes towards drinking water that is "nitrate-free" versus "nitrate-safe" (i.e. below 10 ppm nitrate-N). For the replacement cost methods, the median cost estimate increases when observed responses are accounted for (\$0.039 per kg N; model W4), as opposed to assuming that all households adopt the least-cost avoidance option (\$0.023 per kg N; model W3). These costs increase further when the health impacts of "doing nothing" are estimated (models W5 and W6). When the health impacts are valued based on premature mortalities-approach (model W5), the median cost is \$0.044 per kg N, whereas the median cost is \$0.077 when the health impacts are valued using a lost QALYs-approach. In contrast, the estimated costs of $PM_{2.5}$ exposure are greater when based on a premature mortalities-approach (median = \$1.49 per kg N; model A1) than a lost QALYs-approach (median = \$0.28 kg N; model A2).

Similar to Keeler et al. (2016), we found that the location of N application creates variation in the estimates of the SCN (Fig. S3). N applied in the Central Sands and Southeastern regions of MN is more likely to cause groundwater nitrate contamination as compared to other regions of the state. Also, these regions of the state heavily rely on groundwater for their water supply, whereas the Twin Cities metropolitan region relies on surface water. In contrast, damages of air pollution from NH_3 and NO_x emissions are disproportionately greater for N applied in the Twin Cities metropolitan region. Since we used a spatially constant emissions factor and social cost of carbon, the social cost of N_2O emissions are spatially homogeneous. The benefits of increased crop yields are also assumed to be constant across the state.

Although multiple parameters drive each model, we found that the uncertainty in a single parameter typically explains most of the variation in the model outputs (Fig. 2). Parameter estimates with wide distributions and large influence on the model are more likely to cause variation in estimates of the SCN. The most sensitive parameters for each model are: Y1–corn price, W1–WTP for NO_3^--free drinking water, W2–WTP for NO_3^--safe drinking water, W3–cost of reverse osmosis, W4–cost of bottled water and cost of digging a new well, W5–VSL, W6–RR of thyroid cancer from NO_3^- in drinking water, A1–VSL, A2–RR of mortality from COPD caused by $PM_{2.5}$ exposure, C1–social cost of N_2O.

3.2. Optimal rates of N fertilizer application

There are diminishing marginal returns to N, in terms of increased crop yields, as the rate of N application increases (Fig. 3). While corn yields are limited by N availability, each additional unit of N has an incrementally smaller benefit. This functional relationship, coupled with a constant marginal cost of N fertilizer, requires farmers to optimize their rate of application such that marginal returns to N are maximized. Increasing rates of fertilizer application beyond the optimal, farmers risk negative marginal returns. We found that the privately optimal rate of N fertilizer application in MN is 165 kg N ha^{-1} for

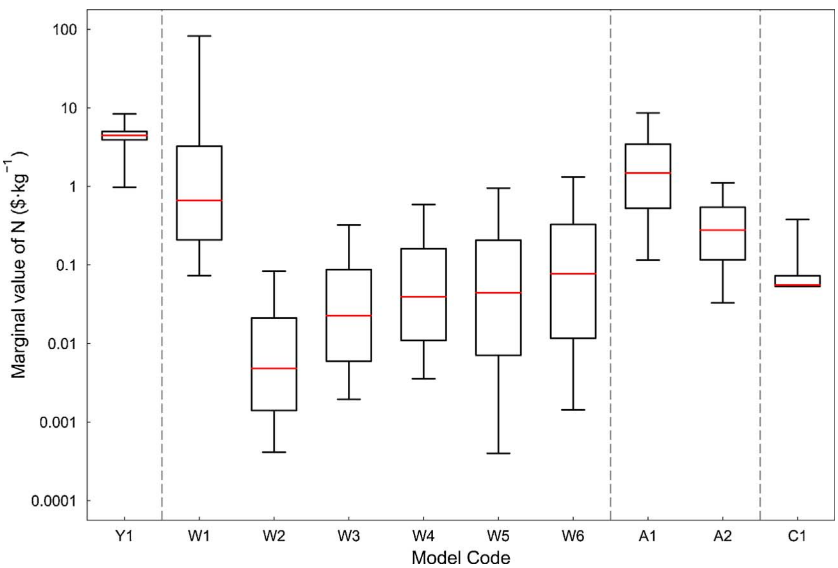


Fig. 1. Boxplots of marginal benefits (Y1) and costs (W1-W6, A1-A2, C1) for each valuation function. Each boxplot indicates a unique valuation function, as identified by the model code on the x-axis. Each boxplot shows the distribution of marginal values across all simulations and all counties. The red line indicates the median, the bottom and top of the box indicate the 25th and 75th percentile, and the whiskers indicate the 5th and 95th percentile.

corn following soybeans (Fig. 3). In 2009, farmers in MN applied 157 kg N ha^{-1} on average (Bierman et al., 2012). This difference is likely due to the fact that the average price of corn used here is $4.18 per bushel, while the price of corn in 2009 was $3.70 per bushel.

Given that the corn yield response saturates near the optimal rate and that the price of N is low relative to the price of corn, marginal returns are highly inelastic to the rate of application. Thus, marginal decreases in the rate of fertilizer application from the privately (i.e. agronomically) optimal rate will have relatively small impacts on private net returns to N, but larger impacts in reducing social costs. Simply for demonstrative purposes, we show an example of when the SCN is assumed to be $0.50 per kg N, a relatively mid-range estimate. If this

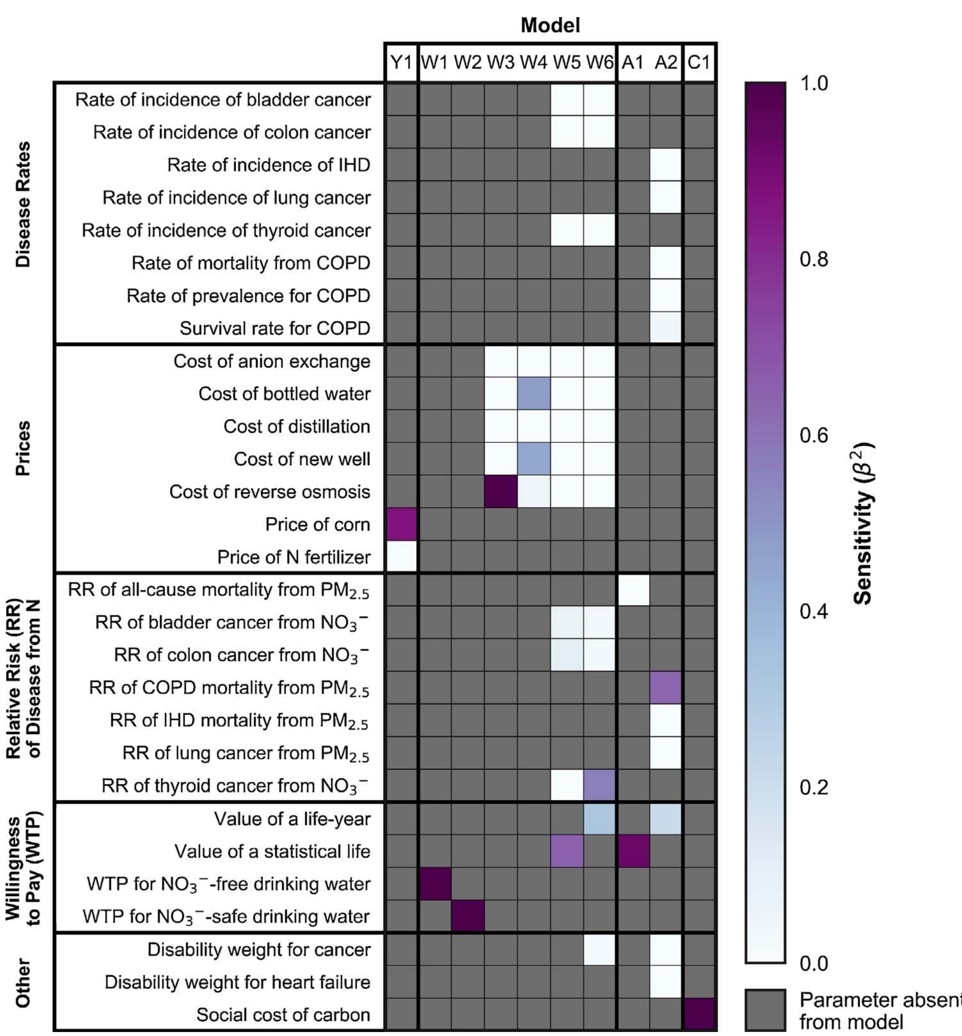


Fig. 2. Parameters' contribution to variance for each valuation function. Each column represents a unique valuation function (described in more detail in Table 1) and each row represents a unique parameter. Parameters are grouped categorically. The sensitivity of a parameter in a given valuation function is indicated by color. Darker color cells represent highly sensitive parameters and lighter color cells represent less sensitive parameters. Dark grey cells indicate parameters that were not included in a model.

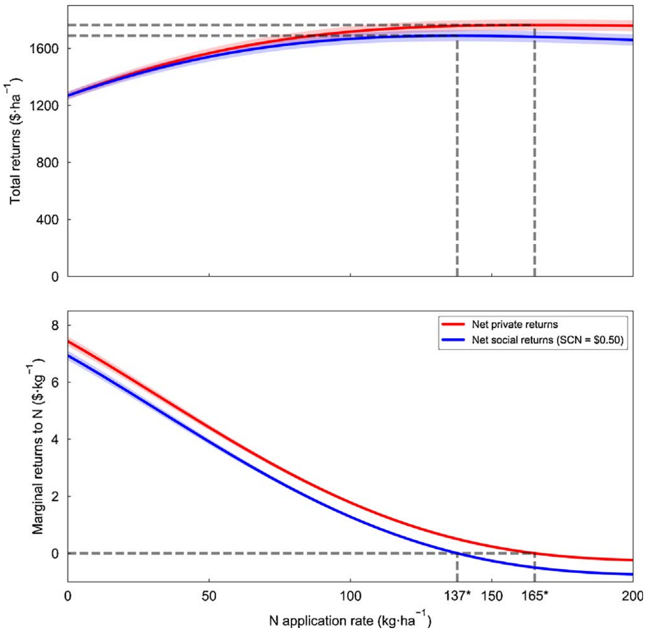


Fig. 3. Returns to N fertilizer as the rate of application increases. Total return to N ($ ha^{-1}) are shown on top and marginal returns to N ($ kg^{-1}) are shown on the bottom. The red line represents net private returns to N and includes the private cost of N, but not the SCN. The blue line represents the net social returns to N and includes both the private and SCN. This figure shows a demonstrative example of when the SCN is assumed to be $0.50, a relatively mid-range estimate. The fill around the lines represents plus and minus one standard error from the mean. The dotted gray lines indicate the N application rate where net private returns and net social returns are maximized.

cost is internalized, the optimal rate of fertilizer application decreases from 165 kg ha^{-1} to 137 kg ha^{-1}. Decreasing the application rate to account for the SCN would decrease private returns by $ 5.95 ha^{-1} and would reduce social costs by $13.50 ha^{-1}, thus creating a net social benefit of $7.55 ha^{-1}. We describe the results for county-specific SCN values in the following paragraph.

Lowering application rates from what is privately optimal results in marginal benefits to society that outweigh the costs to farmers (Fig. 4). The aggregate SCN ranges from $0.05 to over $10 per kg N and socially optimal rates of application ranges from 0 to 161 kg ha^{-1}. Since the maximum marginal net returns to N are approximately $7.44 per kg N, the socially optimal rate of application is 0 kg ha^{-1} when the SCN is greater than or equal to$7.44 per kg N. Under the adoption of socially optimal rates of application, farmers' losses range from 0.01 to 28.1% of their profits and increases in net social benefits range from 0.01 and 65.6%. These ranges are due to both parametric uncertainty and spatial variation. In one possible scenario where the optimal application rate decreases from 165 to 130, farmers lose $10.78 ha^{-1}, but net social welfare increases by $14.11 ha^{-1} (Fig. 4). Since changes in net social welfare already account for private losses, net social gains and private losses are only equal when there is no change in current application rates. As such, social gains only increase as the socially optimal N application rate increases.

We found that the spatial configuration and magnitude of socially optimal N rates shifts depending on the valuation methodologies used to estimate the SCN and the probability distribution of the outputs (Fig. 4). We calculated and compared spatially-explicit socially optimal N application rates for two distinct combinations of methodological approaches. The first approach evaluates health impacts based on lost QALYs, while the second approach evaluates health impacts according to the increase of premature mortalities (Fig. 4). The SCN for the top row of Fig. 4 (QALYs based valuation) is the sum of the outputs from models W6, A2, and C1. The SCN for the bottom row of Fig. 4 (premature mortalities based valuation) is the sum of models W5, A1, and C1. The benefits for both rows were calculated using model Y1. When health impacts are evaluated using QALYs, the highest SCN occur in the central sands region of MN. When health impacts are evaluated using premature mortalities, the highest SCN occur in the Twin Cities metropolitan and southeastern regions. Also, the magnitude of the SCN are greater under the premature mortalities methodology than the QALYs-based methodology. Each column in Fig. 4 displays estimates of the SCN at different percentiles along the cumulative density function (CDF) of SCN model outputs from the Monte Carlo simulation. As the probability on the CDF shifts increases, the magnitude of the SCN increases, but the relative spatial configuration remains the same.

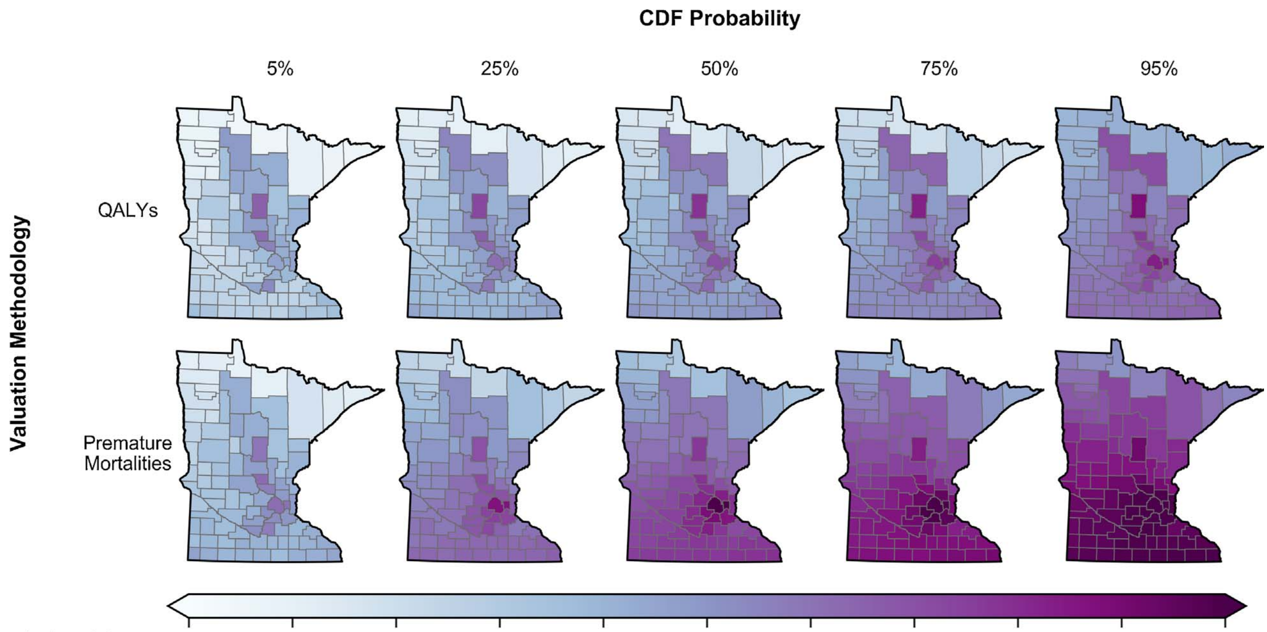
4. Discussion

Our work demonstrates an actionable strategy to manage tradeoffs between agricultural production, air and water quality, and climate change mitigation. We show that socially optimal N application rates would greatly reduce the SCN, with a range of costs to farmers. Our results build on past assessments of the SCN (Sutton et al., 2011; Gu et al., 2012; Kanter et al., 2015; Sobota et al., 2015; Keeler et al., 2016) by characterizing the probability distribution of the costs and benefits of N and explicitly identifying potential policy implications for agricultural management. Our estimated damage costs are lower than these previously published estimates, probability due to lower population exposure to N loss in MN than for analyses in other regions. Similar to Keeler et al. (2016), we found that the SCN vary depending on the location of application and that some regions of MN are more vulnerable to damages of N than others. The spatial distribution of the SCN also varies based on the valuation methodologies used to estimate it. We therefore recommend that managers account for this spatial heterogeneity in the SCN and implement socially optimal N rates specific to the location of application.

Spatial variation in the SCN has important implications for equity. N applied in the north-central and southeastern regions of MN disproportionately affects rural communities by damaging water quality, while N applied in the Twin Cities metropolitan region disproportionately affects urban communities by damaging air quality (Fig. S3). The spatial configuration of the regions with the highest SCN varied depending on how health impacts were valued. Evaluating health impacts based on premature mortalities resulted in the costs of damages to air quality (median = $1.49 kg N^{-1}) far outweighing the costs of damages to water quality (median = $0.044 kg N^{-1}), therefore creating greater incentives to mitigate the SCN in urban regions (Fig. 4). In comparison, when health impacts were quantified based on lost QALYs, there is greater overlap in the magnitude of the costs of damages to air quality (median = $0.28 kg N^{-1}) and water quality (median = $0.077 kg N^{-1}) with some counties having higher costs of damages to water quality than air quality. Rabl (2003) contends that premature mortalities may not be an appropriate metric in this context because the cost of health impacts, especially from air pollution, may be overestimated in comparison to using lost QALYs.

Furthermore, by recognizing uncertainty in estimates of the SCN, decision-makers can select varying levels of caution in determining optimal N rates. For example, a manager who is more skeptical of these estimates may assume an SCN at the 25th percentile of its probability distribution (Fig. 4). In contrast, a manager who is more cautious may assume an SCN at the 75th percentile. For this reason, we do not prescribe a singular optimal rate for each county, but rather allow managers to apply their own preferences to the decision-making process. However, whatever risk preference is applied, managers should recognize that there is uncertainty in their applied estimate and that they still may be under- or over-estimating the true SCN.

Our comparisons of sources of uncertainty (Fig. 2) illuminate priorities for future research. Parameters related to actual market prices, relative risk of health impacts, the value of health impacts, emerged as



Marginal social cost of N ($\$\cdot kg^{-1}$)	0.05	0.08	0.14	0.25	0.42	0.71	1.20	2.04	3.47	5.89	10.00
Socially optimal N app rate ($kg\cdot ha^{-1}$)	161	159	155	149	141	130	114	94	66	26	0
Private loss under socially optimal N rate ($\$\cdot ha^{-1}$)	0.09 (0.01%)	0.25 (0.01%)	0.68 (0.04%)	1.79 (0.1%)	4.44 (0.3%)	10.78 (0.6%)	25.34 (1.4%)	58.24 (3.3%)	134.08 (7.6%)	321.82 (18.2%)	495.40 (28.1%)
Social gain under socially optimal N rate ($\$\cdot ha^{-1}$)	0.10 (0.01%)	0.27 (0.02%)	0.76 (0.04%)	2.06 (0.1%)	5.46 (0.3%)	14.11 (0.8%)	35.44 (2.0%)	86.82 (4.9%)	208.68 (11.8%)	497.65 (28.2%)	1,156.60 (65.6%)

Fig. 4. Policy implications of internalizing the social costs of nitrogen (SCN) in each county in MN. The top row of maps represents estimates of the SCN as the sum of the outputs from models where quality-adjusted life-years (QALYs) were used to evaluate health impacts from exposure to N (models W5, A1, and C1) and the bottom row of maps represents estimates of the SCN as the sum of the outputs the models where premature mortalities were used (models W6, A2, and C1). Each column represents a different estimate of SCN, drawn from percentiles of its cumulative distribution frequency (CDF). The colors are associated with values for four co-varying variables: marginal social cost of N ($ kg^{-1}), social optimal N application rate (kg ha^{-1}), private loss under socially optimal N application rate ($ ha^{-1}), and net social gain under socially optimal N application rate ($ ha^{-1}). Although there is wide variation in estimates of the SCN, the socially optimal rates are always lower than the privately optimal rate.

key drivers of variance in the costs and benefits of N (Fig. 2). Uncertainty in these parameters is caused by different factors. Market prices are more certain, but fluctuate over time and by location, therefore creating risk in long-term planning. Epidemiological research on the relative risk of N-related health impacts is still inconsistent, but is continuing to develop. Estimates of the value of health impacts are highly contentious (Mrozek and Taylor, 2002) and will likely always remain uncertain. Further research to develop a better understanding of these parametric relationships is one way to reduce uncertainty in future assessments of the SCN.

Our aggregated estimates of the SCN are likely to be conservative. First, we omitted several other social costs associated with N fertilizer application, due to limited understanding of these impacts and the data constraints. In particular, a significant portion of N fertilizer applied in MN is exported to freshwater and coastal ecosystems, which may cause eutrophication and hypoxia (Schlesinger, 2009). The economic impacts of these changes in ecosystem functioning are poorly understood and precluded us from monetizing the social costs of N lost to surface water (Rabotyagov et al., 2014). Second, due to computational constraints and limited understanding of the N cycle, we only estimated the SCN associated with the first transformation of N from fertilizer to aquatic and atmospheric pools. Accounting for further transformations in the N cascade (see Galloway et al., 2003) would likely increase estimates of the SCN. Third, we assumed that the marginal SCN remains constant as the rate of fertilizer application increases. According to field studies however, marginal N loss increases as application rates increase (Jaynes et al., 2001; Bouwman et al., 2002; Shcherbak et al., 2014). Thus, it is likely that the marginal SCN in fact increases as application rates increase and that we underestimated the SCN at high rates of application. And fourth, because of a limited understanding of the epidemiological impacts of exposure to N in drinking water, we likely omitted several adverse health impacts that may result from NO_3^- groundwater contamination, such as potential birth defects (Brender et al., 2013; Brender and Weyer, 2016).

We explicitly focused here on parametric uncertainty, but did not include other sources of uncertainty. Uncertainty in the data inputs that drive the models, such as Census data, or uncertainty due to the resolution of the data (i.e. county-level) may create greater uncertainty in the SCN (Refsgaard et al., 2007). We also only focused on uncertainty in the valuation of the SCN and ignored uncertainty that may have propagated from the methods used to estimate exposure to elevated concentrations of different forms of N loss. Moreover, we did not account for diversity in the types of corn grown or farm management practices across the state and assumed that all farms were conventional and homogeneous. These omissions lead us to believe that uncertainty in the SCN is in fact much greater than what we quantified in this analysis.

Effective management of nitrogen (N) fertilizer is central to enhancing agricultural productivity, while improving water and air quality and mitigating climate change (Kanter et al., 2016). Despite the complex biogeochemistry of N and the multitude of ways in which it affects human well-being, our work shows that it is increasingly tractable to quantify and assess the tradeoffs between the costs and benefits

of N at decision-relevant scales. We believe that decision-makers equipped with this information can more effectively prioritize and implement actionable strategies to internalize the SCN and address these challenges. Although uncertainty is inherent when using non-market valuation models to estimate the value of these costs and benefits, illuminating the sources of uncertainty and sensitivity of assumptions and parameters will increase the credibility of this information in decision-making. Despite this range of uncertainty, however, we conclude that internalizing the SCN and deceasing rates of N fertilizer application will result in large benefits to society.

Author contributions

B.L.K and J.D.G. designed the study; J.D.G. performed the analyses and created the figures; B.L.K, J.D.G., and T.H.R. wrote the paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.agee.2017.12.002.

References

Bierman, P.M., Rosen, C.J., Venterea, R.T., Lamb, J.A., 2012. Survey of nitrogen fertilizer use on corn in Minnesota. Agric. Syst. 109, 43–52.
Bouwman, A., Boumans, L., Batjes, N., 2002. Estimation of global NH_3 volatilization loss from synthetic fertilizers and animal manure applied to arable lands and grasslands. Global Biogeochem. Cycles 16, 8-1-8-14.
Bouwman, A., Kram, T., Klein Goldewijk, K., 2006. Integrated modelling of global environmental change. Overview Image 2.
Brender, J.D., Weyer, P.J., 2016. Agricultural compounds in water and birth defects. Curr. Environ. Health Rep. 1–9.
Brender, J.D., Weyer, P.J., Romitti, P.A., Mohanty, B.P., Shinde, M.U., Vuong, A.M., Sharkey, J.R., Dwivedi, D., Horel, S.A., Kantamneni, J., 2013. Prenatal nitrate intake from drinking water and selected birth defects in offspring of participants in the National Birth Defects Prevention Study. Environ. Health Perspect. 121, 1083.
Compton, J.E., Harrison, J.A., Dennis, R.L., Greaver, T.L., Hill, B.H., Jordan, S.J., Walker, H., Campbell, H.V., 2011. Ecosystem services altered by human changes in the nitrogen cycle: a new perspective for US decision making. Ecol. Lett. 14, 804–815.
Crutchfield, S.R., Cooper, J.C., Hellerstein, D., 1997. Benefits of Safer Drinking Water: The Value of Nitrate Reduction. United States Department of Agriculture, Economic Research Service.
De Klein, C., Novoa, R.S., Ogle, S., Smith, K.A., Rochette, P., Wirth, T.C., McConkey, B.G., Mosier, A., Rypdal, K., Walsh, M., 2006. N2O emissions from managed soils, and CO2 emissions from lime and urea application. IPCC Guidelines for National Greenhouse Gas Inventories 4. pp. 1–54 (Prepared by the National Greenhouse Gas Inventories Programme).
Erisman, J.W., Galloway, J.N., Seitzinger, S., Bleeker, A., Dise, N.B., Petrescu, A.R., Leach, A.M., de Vries, W., 2013. Consequences of human modification of the global nitrogen cycle. Phil. Trans. R. Soc. B : Biol. Sci. 368, 20130116.
Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., 2005. Global consequences of land use. Science 309, 570–574.
Galloway, J.N., Aber, J.D., Erisman, J.W., Seitzinger, S.P., Howarth, R.W., Cowling, E.B., Cosby, B.J., 2003. The nitrogen cascade. Bioscience 53, 341–356.
Galloway, J.N., Townsend, A.R., Erisman, J.W., Bekunda, M., Cai, Z., Freney, J.R., Martinelli, L.A., Seitzinger, S.P., Sutton, M.A., 2008. Transformation of the nitrogen cycle: recent trends, questions, and potential solutions. Science 320, 889–892.
Gu, B., Ge, Y., Ren, Y., Xu, B., Luo, W., Jiang, H., Gu, B., Chang, J., 2012. Atmospheric reactive nitrogen in China Sources, recent trends, and damage costs. Environ. Sci. Technol. 46, 9420–9427.
Iowa State University Agronomy Extension and Outreach, 2017. Corn Nitrogen Rate Calculator.
Jaynes, D., Colvin, T., Karlen, D., Cambardella, C., Meek, D., 2001. Nitrate loss in subsurface drainage as affected by nitrogen fertilizer rate. J. Environ. Qual. 30, 1305–1314.
Kanter, D.R., Zhang, X., Mauzerall, D.L., 2015. Reducing nitrogen pollution while decreasing farmers' costs and increasing fertilizer industry profits. J. Environ. Qual. 44, 325–335.
Kanter, D.R., Zhang, X., Howard, C.M., 2016. Nitrogen and the Sustainable Development Goals.
Keeler, B.L., Polasky, S., 2014. Land-use change and costs to rural households: a case study in groundwater nitrate contamination. Environ. Res. Lett. 9, 074002.
Keeler, B.L., Gourevitch, J.D., Polasky, S., Isbell, F., Tessum, C.W., Hill, J.D., Marshall, J.D., 2016. The social costs of nitrogen. Sci. Adv. 2, e1600219.
Kusiima, J.M., Powers, S.E., 2010. Monetary value of the environmental and health externalities associated with production of ethanol from biomass feedstocks. Energy Policy 38, 2785–2796.
Lewandowski, A., Montgomery, B., Rosen, C., Moncrief, J., 2008. Groundwater nitrate contamination costs: a survey of private well owners. J. Soil Water Conserv. 63, 153–161.
Marten, A.L., Newbold, S.C., 2012. Estimating the social cost of non-CO 2 GHG emissions: methane and nitrous oxide. Energy Policy 51, 957–972.
Matson, P.A., Parton, W.J., Power, A., Swift, M., 1997. Agricultural intensification and ecosystem properties. Science 277, 504–509.
Maupin, M.A., Kenny, J.F., Hutson, S.S., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2014. Estimated Use of Water in the United States in 2010. U.S. Geological Survey Circular 1405.
Mrozek, J.R., Taylor, L.O., 2002. What determines the value of life? A meta-analysis. J. Policy Anal. Manage. 21, 253–270.
Pennington, D.N., Dalzell, B., Nelson, E., Mulla, D., Taff, S., Hawthorne, P., Polasky, S., 2017. Cost-effective land use planning: optimizing land use and land management patterns to maximize social benefits. Ecol. Econ. 139, 75–90.
Polasky, S., Nelson, E., Pennington, D., Johnson, K.A., 2011. The impact of land-use change on ecosystem services, biodiversity and returns to landowners: a case study in the State of Minnesota. Environ. Resour. Econ. 48, 219–242.
Porcher, E., 1989. Groundwater Contamination Susceptibility (Minnesota: Minnesota Pollution Control Agency). Ground Water and Solid Waste Division, Program Development Section.
Rabl, A., 2003. Interpretation of air pollution mortality: number of deaths or years of life lost? J. Air Waste Manag. Assoc. 53, 41–50.
Rabotyagov, S., Kling, C., Gassman, P., Rabalais, N., Turner, R., 2014. The economics of dead zones: causes, impacts, policy challenges, and a model of the Gulf of Mexico hypoxic zone. Rev. Environ. Econ. Policy 8 (1), 58–59 (ret024).
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – a framework and guidance. Environ. Model. Softw. 22, 1543–1556.
Saltelli, A., Ratto, M., Tarantola, S., Campolongo, F., 2005. Sensitivity analysis for chemical models. Chem. Rev. 105, 2811–2828.
Schlesinger, W.H., 2009. On the fate of anthropogenic nitrogen. Proc. Natl. Acad. Sci. U. S. A. 106, 203–208.
Shcherbak, I., Millar, N., Robertson, G.P., 2014. Global metaanalysis of the nonlinear response of soil nitrous oxide (N_2O) emissions to fertilizer nitrogen. Proc. Natl. Acad. Sci. U. S. A. 111, 9199–9204.
Sobota, D.J., Compton, J.E., McCrackin, M.L., Singh, S., 2015. Cost of reactive nitrogen release from human activities to the environment in the United States. Environ. Res. Lett. 10, 025006.
Stehfest, E., Bouwman, L., 2006. N2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. Nutr. Cycl. Agroecosyst. 74, 207–228.
Sutton, M.A., Howard, C.M., Erisman, J.W., Billen, G., Bleeker, A., Grennfelt, P., van Grinsven, H., Grizzetti, B., 2011. The European Nitrogen Assessment: Sources, Effects and Policy Perspectives. Cambridge University Press.
Tessum, C.W., Hill, J.D., Marshall, J.D., 2017. InMAP: A model for air pollution interventions. PLoS One 12, e0176131.
U.S. Department of Agriculture − National Agricultural Statistics Service, 2013. Quick Stats.
U.S. Environmental Protection Agency, 2011. National Emissions Inventory: Technical Support Document.
U.S. Interagency Working Group, 2015. Technical support document: technical update of the social cost of carbon for regulatory impact analysis under executive order 12866. Interagency Working Group on Social Cost of Carbon. United States Government, Washington, DC.
van Grinsven, H.J., Rabl, A., de Kok, T.M., 2010. Estimation of incidence and social cost of colon cancer due to nitrate in drinking water in the EU: a tentative cost-benefit assessment. Environ. Health 9, 58.
Vitousek, P.M., Aber, J.D., Howarth, R.W., Likens, G.E., Matson, P.A., Schindler, D.W., Schlesinger, W.H., Tilman, D.G., 1997. Human alteration of the global nitrogen cycle: sources and consequences. Ecol. Appl. 7, 737–750.
Ward, M.H., Kilfoy, B.A., Weyer, P.J., Anderson, K.E., Folsom, A.R., Cerhan, J.R., 2010. Nitrate intake and the risk of thyroid cancer and thyroid disease. Epidemiology 21, 389.
Wegner, G., Pascual, U., 2011. Cost-benefit analysis in the context of ecosystem services for human well-being: a multidisciplinary critique. Global Environ. Change 21, 492–504.